Nature Environment and Pollution Technology
An International Quarterly Scientific Journal

p-ISSN: 0972-6268
(Print copies up to 2016)
e-ISSN: 2395-3454

Vol. 22 | No. 4 | pp. 1857-1866 | 2023

Original Research Paper

https://doi.org/10.46488/NEPT.2023.v22i04.013

Open Access Journal

The Effect of Government Subsidies on Innovation Capability of the New Energy Vehicle Industry

Guixing Yang*(**)†
*Innovation College, North-Chiang Mai University, Chiang Mai, 50230, Thailand
**School of Finance and Economics, Fuzhou Technology and Business University, Fuzhou, 350175, China
†Corresponding author: Guixing Yang; g636501038@northcm.ac.th

Nat. Env. & Poll. Tech.
Website: www.neptjournal.com

Received: 04-04-2023
Revised: 15-05-2023
Accepted: 16-05-2023

Key Words:
Government subsidies
Innovation capability
New energy vehicle
Network DEA

ABSTRACT

Countries all over the world are paying attention to the growth of the new energy vehicle industry and implementing various subsidy policies to stimulate industry development to enhance the new energy vehicle industry's innovative capability. This study uses a network DEA model to analyze China's new energy vehicle industry's technological innovation capability, decomposing it into two stages: technology development and innovation transformation, and calculating the innovation capability level of China's new energy vehicle industry from 2012 to 2017. The findings show that due to a disconnect between the efficiency of the technology development stage and the efficiency of the innovation transformation stage, innovation technology cannot serve business operations, resulting in China's new energy vehicle industry's overall low level of innovation capability. Based on this, an IT3SLS analysis of the factors influencing innovation capability and phase-by-phase efficiency reveals that while China's new energy vehicle industry's subsidy policy has historically failed to significantly improve innovation capability, there is a complementary/substitution effect between labor input, corporate capital, and government subsidies. Based on the findings of this study, important policy recommendations are made to further develop the technological capabilities of the new energy vehicle industry in the context of China's present new energy policy.

INTRODUCTION

The worldwide car industry is transitioning away from internal combustion engines and toward new energy sources such as pure electric and hybrid drivetrains. More and more governments around the world are discovering that a single energy mix is incompatible with national strategic security, particularly in countries with limited oil resources (Sun & Ju 2022). At the same time, some emerging developing countries believe that there is still a significant gap in internal combustion engine technology for their national automobile manufacturers to catch up to established automobile companies in developed countries, so they see the new energy vehicle revolution as a historic opportunity to develop their automobile manufacturing industries (Wang et al. 2023). The pressure from global warming, as well as the growth of business, has encouraged industrialized countries to actively create their new energy vehicle industry.

In brief, many countries aim to progressively phase out traditional fuel cars as the primary source of transportation, allowing their automobile manufacturing sectors to grow. Technological innovation activities have a degree of revenue uncertainty and externality, and the incentive for businesses to innovate under market regulation is insufficient. It is difficult to achieve the optimal allocation of innovation resources without government intervention, guidance, and support. As a result, some nations have enacted measures to encourage the growth of the new energy vehicle industry. For example, in November 2010, the Chinese government enacted a policy designating new energy vehicles as a national strategic developing industry, and the entire industrial chain has been heavily subsidized (Liu & Kokko 2013).

Government subsidies, on the other hand, have always been a contentious policy tool for promoting the development of the new energy vehicle industry. In China, some enterprises have obtained government subsidies through rent-seeking and fraud due to insufficient policy coordination, information disclosure, supervision, and management in the new energy vehicle industry, raising questions about the rationality, effectiveness, and efficiency of government subsidies in supporting technological innovation activities (Zhang & Cai 2020). Therefore, many scholars have previously focused on the effects of government subsidies on relevant firms' innovation inputs, innovation outputs, and firm performance and attempted to prove the mechanisms of government subsidies on firms' innovation activities using a variety of empirical methods. To some extent, this research has enriched theories about industrial policy.

However, the measures of innovation input, output, and firm performance serve only as partial indicators of firm innovation capability at a specific stage. Previous studies have rarely considered these three measures together as a comprehensive representation of innovation capability for new energy vehicle firms (Chen et al. 2021, Yang et al. 2021).

In contrast, the government places greater emphasis on the overall enhancement of enterprise innovation capacity compared to the efficacy of these individual stages.

Many governments have made "increasing technological innovation capability" a high priority when establishing their subsidy policies, demonstrating the importance of technological innovation in the long-term development of the new energy vehicle industry. Government subsidies, according to policymakers, are designed to strengthen businesses' innovation capabilities so that they can sustain their competitiveness over time and support the seamless running of the national industrial supply chain. The success of government subsidy policies can be further debated by determining whether or not the industry's innovation capabilities have increased. By empirically analyzing the influence of government subsidy policy on enterprise innovation capability, I hope to construct innovation capability evaluation indexes for enterprises in the new energy vehicle industry, allowing them to more accurately measure innovation capability and improve the evaluation of the effectiveness of government subsidy policy.

PAST STUDIES AND THE ORETICAL BASIS

Past Studies

Because of the many study backgrounds, research objects, and research techniques, the relationship between government subsidies and technological innovation has yet to develop a coherent conclusion, and current studies have roughly produced the following four views: (1) Promotional function. According to this viewpoint, government subsidies can compensate for businesses' R&D deficiencies and minimize their R&D risks, allowing them to increase their innovation investment. Government subsidies have both technology-push and demand-pull impacts, lowering private costs of technological innovation and raising private investor returns (Nemet 2009). Based on data from Ireland and Northern Ireland from 1994 to 2002, Hewitt-Dundas and Roper (2010) concluded that government subsidies can enhance the share of enterprises producing innovative inputs as well as boost incremental product innovation and new product developmental innovation behavior. (2) Disincentive function. The presence of government rent-seeking and market-oriented environments, according to this viewpoint, undermines enterprises' innovative conduct. Government subsidies, according to Beason and Weinstein (1996), weaken or eliminate the payoffs of scale and the growth impacts of enterprises to some extent. Clausen (2009) found that government subsidies have a limited crowding-out effect on firms' innovation behavior, i.e., firms may cut their own innovation inputs and lower their innovation output, implying that government subsidies have a negative impact on firms' innovation activities. (3) No significant relationship. Based on data related to the manufacturing industry in West Germany, Bönte (2004) concluded that government subsidies do not affect improving firm productivity by exploring the role of government innovation subsidies on firm productivity and the role of firm innovation inputs on firm survival. Tzelepis and Skuras (2004) analyze data on subsidies for Greek firms and find that government subsidies improve the solvency of firms and positively stimulate firm growth but have no significant effect on improving firm efficiency and profitability. (4) Non-linear relationship. According to this viewpoint, the relationship between business innovation and government subsidies is not linear but rather changes depending on the level of government subsidies. Bergstrom (2000) examined the Swedish government's subsidy to listed companies from 1987 to 1993, finding that the capital subsidy had a positive impact on the "total factor growth rate" in the first year after the subsidy. Still, then, the capital subsidy had a negative impact on the "total factor growth rate." Harris and Trainor (2005) used data from manufacturing firms in Northern Ireland from 1983 to 1998 to divide the technical level of firms. They discovered that the influence of government subsidies on total factor productivity differed depending on the technological level of firms.

Overall, most existing studies on the relationship between government subsidies and company innovation behavior focus on macro, industrial, and other levels, with less research on the new energy vehicle industry. In recent years, due to the rapid development of the new energy vehicle industry, a number of papers on the assessment of the innovation efficiency of the new energy vehicle industry have mushroomed. For example, Li et al. (2019) analyzed the panel data of 148 new energy vehicle-related firms in Zhongguancun, China, from 2005-2015, and the results showed that there was no significant effect of government subsidies on the performance of SMEs. Fang et al. (2020) explored the impact of government subsidies on innovation efficiency among 23 Chinese new energy vehicle firms during 2013-2018, using the DEA-Tobit method to not only assess innovation efficiency but also to analyze the possible impact of government subsidies to some extent. Chen et al. (2022) analyzed the innovation efficiency of China's new energy vehicle supply chain using the NSBM method by analyzing data from 105 new energy vehicle-related listed enterprises in China from 2012 to 2019. They reorganized the way innovation efficiency is assessed in a more systematic perspective. It is easy to see that the innovation assessment efficiency methods in this field of research regarding the new energy vehicle industry have been gradually improved. However, it is worth noting that since previous studies have divergent views on the relationship between government subsidies and firm innovation, this may be due to the different understandings among academics on the relationship between the concepts of innovation inputs, innovation outputs, and firm performance. Therefore, it is necessary to adopt a new perspective to examine the innovation capability of enterprises, which in turn can explore more deeply the utility of innovation subsidies on the innovation capability of new energy vehicle enterprises.

In summary, a large number of theoretical and empirical studies have been conducted by scholars, and a certain research base has been formed as the research content continues to deepen. However, since the impact of government subsidies on innovation capability has not been discussed in detail, the existing research can be further expanded from the following perspectives: Unlike the innovation input, innovation output, and enterprise performance, the innovation capability of enterprises is the value embodiment of the enterprise innovation process, and the innovation capability of the new energy vehicle industry can be analyzed through the innovation value chain theory. Based on this, this study will examine enterprise innovation capability and the value chain theory of technological innovation in the new energy industry, investigate the impact of government subsidies on innovation capability, broaden the connotation and extension of enterprise innovation capability, and thus more thoroughly discuss the impact of government subsidies on the new energy vehicle industry's innovation capability.

Innovation Value Chain Theory and Innovation Capability

Innovation value chain theory was first proposed by Hansen and Birkinshaw (2007), who combined technology innovation theory and value chain theory to present innovation as a process consisting of multiple stages involving idea generation, development, and concept diffusion throughout the innovation value chain. In this theoretical framework, the process of realizing the value of technological innovation in a firm involves a complex set of activities from research to development and then from development to transformation of economic results.

Innovation capability is one of an organization's intangible assets, and the organization can also continue innovatively developing that asset. Traditional DEA approaches such as SBM-DEA and DEA-MALMQUIST have been utilized in previous research to assess organizations' innovation capacity (Guan et al. 2006, Wang & Zhang 2018). In general, it continues to break down innovation capability into innovation input, innovation output, and company performance in silos, failing to assess businesses' innovation capability holistically. In the meantime, some researchers have used questionnaires to assess firms' innovation capability (Saunila & Ukko 2014, Le & Lei 2019). While innovation capability can be measured by combining innovation inputs, innovation outputs, and firm performance, the questionnaire method is difficult to overcome due to subjectivity. To assess a firm's innovation capabilities, an integrated perspective and a combination of objective measures are required.

Innovation capability is an integrated measure of innovation inputs, innovation outputs, and business performance from the perspective of the innovation value chain. As a result, the innovation value chain perspective should be introduced in order to assess innovation capability more comprehensively, and this study combines the study of Du et al. (2019) to structure the innovation capability of the new energy vehicle industry into a technology development stage and an innovation transformation stage. The technology development stage encompasses the entire process from an enterprise's initial technology development input to the intermediate innovation output, which includes R&D funding and R&D staff. The innovation transformation stage refers to the process of applying the technology development results to the production of marketable products, commercializing the intermediate innovation results, and forming the economic benefits of the enterprise, which is the continuation of the technology development stage and the key link between the technology innovation results and the market. Its core task is to realize the market value of the intermediate innovation results output. The intermediate innovation output, as the intermediate product of the entire technological innovation activity, is not only the first result of the enterprise's initial innovation inputs but also the foundation for applying to commercial production and forming economic benefits in the later stage, connecting and promoting the mutual promotion and coordinated development of each sub-stage. The process of enterprise technology innovation value realization has apparent two-stage chain network characteristics, as can be shown. Fig. 1 depicts the specific procedure.

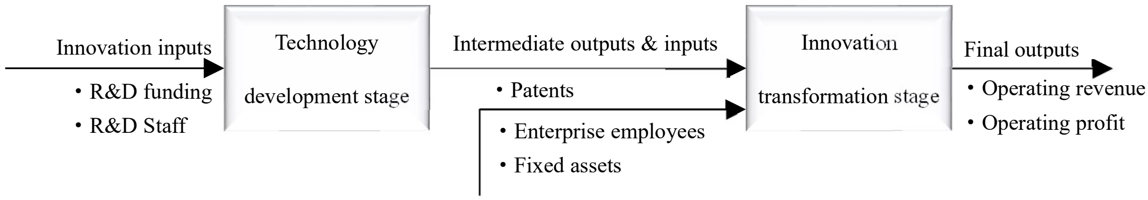

Fig. 1: Deconstruction of innovation capability of new energy vehicle industry.

MATERIALS AND METHODS

Two-Stage Network DEA

Traditional econometric approaches such as regression analysis and simple ratio analysis are not well suited to efficiency measurement activities. Data Envelopment Analysis (DEA) is a more powerful analytical way of testing that is better suited to efficiency measurement activities. DEA is a mathematical method that converts inputs into outputs using linear programming techniques to compare the efficiency of similar organizations or goods. Each decision-making unit (DMU) in DEA is allowed to select any combination of inputs and outputs to maximize its relative efficiency. The ratio of total weighted outputs to total weighted inputs is known as relative efficiency or efficiency score (Zhu 2009). DEA is a typical method for evaluating system efficiency in a nonparametric framework that has been popularized and extensively accepted in numerous study areas since its first application in 1978 (Cook & Seiford 2009). Traditional DEA models can only assess the efficiency of a process by putting input indicators into a "black box" and considering the efficiency of output indicators without taking into account what happens in the "black box," which used to be a benefit of DEA models. This was originally a benefit of DEA models. Still, as academic problems grew more complicated, the requirement to break down the contents of the "black box" prompted the development of network DEA models (Tone & Tsutsui 2009). The new energy vehicle industry's innovation capability spans the entire process, from technological creation through innovation transformation. As a result, a two-stage network DEA model can aid in the "unlocking" of the "black box" of innovation capability assessment. Table 1 shows the unique explanatory factors for the network DEA model, which is based on the study by Du et al. (2019) on innovation capability.

The non-radial SBM two-stage network DEA model proposed by Tone is used to ensure the efficiency of the evaluation model to some extent because the network DEA model may cause the network DEA model to overestimate the efficiency level of the evaluation object if there is over-input or under-output in the network DEA model (i.e., there is non-zero slack). This is shown as follows.

For a set of n decision-making units $DMU_S(j = 1, ..., n)$ with K nodes $(k = 1, \dots, K)$. Let m_k and r_k be the input and output amounts for the node k respectively. (k, h) denotes the connection relation between nodes k and h, and L is the connection set. The observed data are $\{x_j^k \in R_+^{m_k}\}(j = 1, \dots, n; k = 1, \dots, K)$ (DMU_j input quantity at the node), $\{\mathbf{y}_j^k \in R_+^{r_k}\}(j = 1, \dots, n; k = 1, \dots, K)$ (DMU_j output quantity at node k), and $\{\mathbf{z}_j^{(k,h)} \in R_+^{t_{(k,h)}}\}(j = 1, \dots, n; (k,h) \in L$. where $t_{(k,h)}$ is the connection relation (k, h) variable number. In this paper, we adopt the assumption of variable payoffs of scale and define the set of production possibilities $\{(\mathbf{x}^k, \mathbf{y}^k, \mathbf{z}^{(k,h)})\}$ as:

Table 1: Two-stage indicators for deconstructing innovation capability.

Stage	Level 1 Indicators	Level 2 Indicators
Technology development stage	Innovation inputs	R&D funding (10000 yuan)
		R&D staff (persons)
	R&D intermediate outputs	Patent applications (items)
		Increase in value of intangible assets (10000 yuan)
Innovation transformation stage	Commercial inputs	Full-time equivalent of practitioners (persons/year)
		Net value of fixed assets (10000 yuan)
	Commercial outputs	Revenue from main business (10000 yuan)
		Operating profit (10000 yuan)

$$\mathbf{x}^k \geq \sum_{j=1}^{n} \mathbf{x}_j^k \lambda_j^k \left(k=1,\ldots,K\right), \mathbf{y}^k \leq \sum_{j=1}^{n} \mathbf{y}_j^k \lambda_j^k \left(k=1,\ldots,K\right) \ldots(1)$$

$$\mathbf{z}^{(k,h)} = \sum_{j=1}^{n} \mathbf{z}_j^{(k,h)} \lambda_j^k \left(\forall\left(k,h\right)\right)\left(\text{as the output of node } k\right) \quad \ldots(2)$$

$$\mathbf{z}^{(k,h)} = \sum_{j=1}^{n} \mathbf{z}_j^{(k,h)} \lambda_j^h \left(\forall\left(k,h\right)\right)\left(\text{as the input of node } h\right) \quad \ldots(3)$$

$$\sum_{j=1}^{n} \lambda_j^k = 1\left(\forall k\right), \lambda_j^k \geq 0\left(\forall j,k\right) \quad \ldots(4)$$

$\lambda^k \in R_+^n$ denotes the weight corresponding to node $k(k=1,\ldots,K)$ and $\mathrm{DMU}_o(o=1,\ldots,n)$ and can be expressed by:

$$\mathbf{x}_o^k = \mathbf{X}^k \lambda^k + \mathbf{s}^{k-} \left(k=1,\ldots,K\right), \mathbf{y}_0^k = \mathbf{Y}^k \lambda^k - \mathbf{s}^{k+} \left(k=1,\ldots,K\right) \quad \ldots(5)$$

$$\mathbf{e}\lambda^k = 1\left(k=1,\ldots,K\right), \lambda^k \geq 0, \mathbf{s}^{k-} \geq 0, \mathbf{s}^{k+} \geq 0, \left(\forall k\right) \quad \ldots(6)$$

$$\mathbf{X}^k = \left(\mathbf{x}_1^k,\ldots,\mathbf{x}_n^k\right) \in R^{m_k \times n}, \mathbf{Y}^k = \left(\mathbf{y}_1^k,\ldots,\mathbf{y}_n^k\right) \in R^{r_k \times n} \quad \ldots(7)$$

where $\mathbf{s}^{k-}\left(\mathbf{s}^{k+}\right)$ is the input (output) slack variable. For the constraints of the connecting variables, LF is used to connect the nodes, indicating that the connecting variables are free to decide to maintain the continuity of the input and output quantities at the same time, as expressed by the following equation:

$$\mathbf{Z}^{(k,h)} \boldsymbol{\lambda}^h = \mathbf{Z}^{(k,h)} \boldsymbol{\lambda}^k, \left(\forall\left(k,h\right)\right) \quad \ldots(8)$$

$$\mathbf{Z}^{(k,h)} = \left(\mathbf{z}_1^{(k,h)},\ldots,\mathbf{z}_n^{(k,h)}\right) \in R^{t_{(k,h)} \times n} \quad \ldots(9)$$

Considering the possible slackness of the input and output quantities, for a more accurate assessment, the undirected network model is used in this paper, as shown in the following equation.

$$\rho_o^* = \min_{\lambda^k, sk-s^{k+}} \frac{\sum_{k=1}^{K} w^k \left[1 - \frac{1}{m_k}\left(\sum_{i=1}^{m_k} \frac{s_i^k}{x_{i0}^k}\right)\right]}{\sum_{k=1}^{K} w^k \left[1 + \frac{1}{r_k}\left(\sum_{r=1}^{r_k} \frac{s_t^{k+}}{y_{t0}^k}\right)\right]} \quad \ldots(10)$$

Here $\sum_{k=1}^{K} w^k = 1, w^k \geqslant 0(\forall k)$, where w^k, where w^k is the relative weight of node k to indicate the relative importance of that node. Meanwhile, ρ_o^* is defined as the undirected efficiency of the decision unit DMU_0. If $\rho_o^* = 1$, it indicates the overall efficiency of the decision unit DMU_o, and the representation of each node is

$$\rho_k = \frac{1 - \frac{1}{m_k}\left(\sum_{i=1}^{m_k} \frac{s_i^{k-*}}{x_{ii}^k}\right)}{1 + \frac{1}{r_k}\left(\sum_{r=1}^{r_k} \frac{s_r^{k+*}}{y_{r0}^k}\right)} \left(k=1,\ldots,K\right) \quad \ldots(11)$$

Here, $\mathbf{s}^{k-*}$ and $\mathbf{s}^{k+*}$ are the slack variables for the optimal input and optimal output, respectively.

Model of Factors Influencing Innovation Capability

Because the process of innovation is difficult to measure and compute, academics have been sluggish in creating methods for estimating innovation capability. Crepon et al. (1998) proposed the CDM model to solve this problem, which allows for the study of innovation capabilities using knowledge production functions; Aiello and Cardamone(2008) improved the CDM model by establishing a transcendental logarithmic production function model that includes innovation spillover effects. The transcendental logarithmic CDM model is employed as the research model in this study, based on the application of the CDM model and with reference to Aiello and Cardamone's study.

$$\begin{aligned} Cap_{it} &= \alpha_i + \alpha_L \ln L_{it} + \alpha_K \ln K_{it} + \alpha_C \ln C_{it+} \alpha_R \ln R_{it} + \frac{1}{2}\beta_{LL}\left(\ln L_{it}\right)^2 \\ &+ \frac{1}{2}\beta_{KK}\left(\ln K_{it}\right)^2 + \frac{1}{2}\beta_{CC}\left(\ln C_{it}\right)^2 \\ &+ \frac{1}{2}\beta_{RR}\left(\ln R_{it}\right)^2 + \beta_{LK}\ln L_{it}\ln K_{it} + \beta_{LC}\ln L_{it}\ln C_{it} + \beta_{LR}\ln L_{it}\ln R_{it} + \\ &\beta_{KC}\ln K_{it}\ln C_{it} + \beta_{KR}\ln K_{it}\ln R_{it} + \beta_{CR}\ln C_{it}\ln R_{it} + \varepsilon_{it} \end{aligned} \quad \ldots(12)$$

The following four equations, based on Aiello and Cardamone, are added to each factor input cost-sharing equation to make the above model estimation effective in avoiding multicollinearity mistakes among the parameters and control variables.

$$S_{L,it} = \alpha_L + \beta_{LL}\ln L_{it} + \beta_{LK}\ln K_{it} + \beta_{LC}\ln C_{it} + \beta_{LR}\ln R_{it} + \mu_{L,it} \quad \ldots(13)$$

$$S_{K,it} = \alpha_K + \beta_{LK}\ln L_{it} + \beta_{KK}\ln K_{it} + \beta_{KC}\ln C_{it} + \beta_{KR}\ln R_{it} + \mu_{K,it} \quad \ldots(14)$$

$$S_{C,it} = \alpha_C + \beta_{LC}\ln L_{it} + \beta_{KC}\ln K_{it} + \beta_{CC}\ln C_{it} + \beta_{CR}\ln R_{it} + \mu_{C,it} \quad \ldots(15)$$

$$S_{R,it} = \alpha_R + \beta_{LR}\ln L_{it} + \beta_{KR}\ln K_{it} + \beta_{CR}\ln C_{it} + \beta_{RR}\ln R_{it} + \mu_{R,it} \quad \ldots(16)$$

The detailed explanation and calculation of the model are shown in Table 2. The detailed explanation of the variables is as follows.

(1) Labor input. When considering labor input, we should consider not only the wages paid to employees but also other welfare and insurance expenses paid to employees, which are included in the administrative expense account.

(2) Capital investment. Referring to the unified measurement standard in the academic field, the capital input of enterprises is defined as 10% of the total assets of the year.

(3) R&D input. To calculate the cumulative effect of R&D expenditure, we take R&D input = current year R&D input + previous year R&D input × 85%.

(4) Government subsidies. The total amount of government subsidies received by the company includes financial subsidies, financial subsidies, tax reductions and refunds, and so on. The non-current profit and loss of the enterprise's financial statements and other disclosure reports are used as reconciliation information; the cumulative effect of the same R&D input is calculated by taking government subsidies = the current year's government subsidies + the previous year's government subsidies 85%.

Data Source

The initial sample is centered on companies that were listed on the Shanghai and Shenzhen stock exchanges prior to 2012 and whose primary industry is new energy vehicles. After eliminating ST and *ST stocks, as well as businesses with significant missing data, the balanced panel data of 39 publicly traded companies, including BYD and Shanghai Auto, is eventually chosen. Meanwhile, due to the partial absence of the database, only the dataset from 2012-2017 was used in this study to ensure the scientific accuracy of the data. The data in this study comes from the same CHOICE database, CSMAR database, State Intellectual Property Office, and each company's annual reports, with the missing individual data estimated using the interpolation approach. The sample ends in 2017 because CSMAR's innovation data are not available after 2017.

RESULTS

Evaluation of Innovation Capability of the New Energy Vehicle Industry

The data were generated and reported in Table 3 using DeaSolver 13.0 software and the network DEA model to estimate the comprehensive efficiency of 39 new energy vehicle industry enterprises from 2012 to 2017.

Table 3 shows the three efficiency values (average efficiency from 2012 to 2017) of 39 listed new energy industry enterprises, which reflect the overall state of innovation capability as well as efficiency by stage of listed new energy vehicle industry enterprises in China over the last six years. The average value of China's enterprise innovation capability from 2012 to 2017 is 0.2246, which is a relatively low level of innovation capability overall, and the level of innovation capability varies somewhat from year to year. Although the change in innovation capability from 2015 to 2017 has increased, it has not yet achieved the level of innovation capability seen in 2012, showing that the Chinese new energy vehicle industry as a whole is still developing. There is an opportunity for improvement in terms of innovative capability.

From 2012 to 2017, the total efficiency of the innovation transformation stage of firms in China's listed new energy

Table 2: Variable selection and definition of the model.

Variable	Definition	Definition
Innovation Capability	*Cap*	Calculated by two-stage network DEA
Government Subsidies	*R*	The subsidy amount of "government subsidies" in the "non-operating income" account in the annual report of the listed company for the current year + the subsidy amount of the previous year × 85%
Labor investment	*L*	The sum of the enterprise's employee compensation payable and administrative expenses for the year
Capital investment	*K*	Total corporate assets × 10%
R&D investment	*C*	Enterprise current year R&D expenditure + previous year R&D expenditure × 85%
Share of labor investment	S_L	L/Cap
Share of capital investment	S_K	K/Cap
Share of R&D investment	S_C	C/Cap
Share of government subsidies	S_R	R/Cap

Table 3: Innovation capacity of China's new energy vehicle industry, 2012-2017.

	2012	2013	2014	2015	2016	2017	Mean
Innovation capability	0.2510	0.1952	0.2085	0.2044	0.2123	0.2419	0.2189
Technology development stage	0.2637	0.2564	0.2586	0.2304	0.1975	0.1870	0.2322
Innovation transformation stage	0.2969	0.2119	0.2257	0.2404	0.2567	0.2948	0.2544

industry outperformed the technology development stage. The efficiency of the technology development stage is in the range [0.1870, 2637], while the efficiency of the innovation transformation stage is in the range [0.2119, 2969], with the efficiency of the innovation transformation stage being about 12.1% higher than the efficiency of the technology development stage over the last 6 years. In the past 6 years, it is easy to find that the listed Chinese enterprises in the new energy industry have emphasized the potential commercial value of enterprise technology innovation and insisted on direct market-oriented innovation transformation activities, and overall innovation transformation efficiency has remained stable. At the same time, there is a significant mismatch between the technology development stage and the innovation transformation stage of Chinese listed new energy industry enterprises, as well as a gap in efficiency between the two stages. Simultaneously, the efficiency level of the technology development stage has been steadily decreasing from 2012 to 2017, indicating that enterprise technology development activities have shifted away from solving actual technical problems and meeting market demand, lowering overall innovation capability.

Empirical Analysis of the Impact of Government Subsidies on the Innovation Capability of the New Energy Vehicle Industry

The study is based onAiello and Cardamone (2008). It uses iterative three-stage least squares (IT3SLS) optimization to eliminate the negative impact on estimation in the absence of some cost share equations. It also examines the innovation capacity, the efficiency of the technology development stage, and the efficiency of the results of the innovation transformation stage.

Table 4 shows the statistical findings of the analysis using STATA 13.0. The factors influencing innovation capabilities and the efficiency of technology development and transformation stages in the IT3SL3 estimation pass the t-test at all three stages, and the estimated values are all negative, as can be seen from the model estimation results. Labor and capital investment are negatively correlated with innovation capability, according to the α_L and α_K Results. The results of α_L and α_K indicate that innovation capability is negatively correlated with innovation capability, indicating that innovation capability is neither labor-intensive nor capital-intensive. α_R Shows that the Chinese government's subsidies for new energy vehicles have not only failed to improve the innovation capability of enterprises in the past but also inhibited the improvement of innovation capability. Even though several studies have found that government subsidies have a considerable positive impact on enterprises' innovation inputs or outputs, they have mostly neglected the impact of government subsidies on innovation capability. The findings of this study imply that

Table 4: Innovation capacity and stage efficiency IT3SLS results.

	Innovation capacity		Technology Development Efficiency		Innovation Transformation Efficiency	
	Estimated	t	Estimated	t	Estimated	t
α_L	-0.3919***	-4.76	-0.3501***	-4.17	-0.4960***	-5.34
α_K	-0.3429***	-4.46	-0.3063***	-3.91	-0.4177***	-4.82
α_C	0.2178	1.44	-0.3633**	-2.36	0.4360***	2.56
α_R	-0.2512**	-2.52	-0.1798*	-1.77	-0.1939*	-1.72
β_{LL}	0.0767	1.52	-0.0991*	-1.93	0.1984***	3.49
β_{KK}	0.0521	1.55	-0.0426	-1.24	0.1067***	2.82
β_{CC}	0.1171***	3.82	0.0847***	2.71	0.1446***	4.19
β_{RR}	0.0381*	1.9	0.0374*	1.83	0.0433**	1.92
β_{LK}	0.0199	0.49	0.0794*	1.89	-0.0244	-0.53
β_{LC}	-0.0910***	-2.66	0.0120	0.34	-0.1640***	-4.26
β_{LR}	0.0525	1.59	0.0639*	1.9	0.0572	1.54
β_{KC}	-0.0213	-0.66	-0.0122	-0.37	-0.0006	-0.02
β_{KR}	-0.0268	-1.44	-0.0034	-0.18	-0.0544***	-2.59
β_{CR}	-0.0376	-1.36	-0.0747***	-2.65	-0.0267	-0.86
Sample size	227		227		227	
R^2	0.5086		0.6766		0.3322	

Note: ***, **, * denote 1%, 5%, 10% significant levels, respectively the current Chinese government subsidy program has a spillover impact. Government subsidy policy is not always effective due to externalities, and the Chinese new energy vehicle industry has generated a large number of fraudulent subsidies at the early stage of development. Enterprises seeking government subsidies efficiently fail to invest the funds in R&D activities, resulting in low efficiency at the technology development stage and low consumer recognition as a result of transmission to the market, resulting in low efficiency at the innovation transformation stage.

It can be noted from the results in Table 4 that the indicators of substitution complementarity associated with government subsidies, such as β_{LR}, β_{CR}, and β_{KR}, have different degrees of impact on innovation capacity and stage efficiency. As Morishima (1967) argues for the elasticity, when the elasticity value is positive (negative), the two inputs are substitutes (complementary), and it is possible to measure how the 2 input variables affect the change in output variables. β_{KR}, β_{CR} have a negative overall impact size, demonstrating a substitution effect between government subsidies and businesses' own capital and innovation investment, implying that government subsidies have a negative influence on firms' own capital and innovation investment. This suggests that government subsidies have a crowding-out effect on firm investment and that the Chinese government's subsidy strategy for the new energy vehicle industry still has a lot of space for improvement. Government subsidies and labor investment have complimentary impacts on the technological development stage and the influence of β_{LR} is not considerable in the innovation capability and innovation transformation stages, but the overall trend is good. This finding suggests that the success of government subsidies for improving a firm's innovation capacity is dependent on whether the firm has the necessary expertise to efficiently translate the associated innovation inputs into innovation outputs. Due to the existence of the substitution/complementarity impact, the Chinese government must and can optimize its new energy vehicle industrial policy to some extent.

DISCUSSION

This study re-examines the innovation capability of Chinese new energy vehicle enterprises from the perspective of the innovation value chain. It analyzes the influencing factors by introducing the CDM model. The introduction of the innovation value chain theory can help to enhance the understanding of the entire innovation process of the enterprise and no longer confine the innovation capability of the enterprise to a certain stage of innovation input, innovation output, or enterprise performance. This study integrates them through a two-stage network DEA model and conducts a systematic evaluation. Some previous studies have also noticed that the evaluation of innovation capability needs to adopt an integrated perspective. Based on this, this study further strengthens the explanatory power of enterprise innovation capability by introducing the innovation value chain theory. At the same time, the introduction of the CDM model focuses on the substitution and complementary effects between different variables, making up for the shortcomings of previous studies that only focused on linear relationships between variables (Li et al. 2019, Chen et al. 2021), and provides a certain basis for providing more policy tools.

When nations throughout the world realized the necessity of expanding the new energy vehicle industry, they made innovation capability a focal point of their industrial development. They implemented key industrial subsidy programs to help the new energy vehicle industry grow. Previous studies, on the other hand, have typically focused solely on the impact of subsidy policies on innovation inputs, innovation outputs, and enterprise performance in enterprises' innovation activities, and the inconsistency of research backgrounds has often resulted in conflicting conclusions. Firm innovation capabilities must be considered systematically; otherwise, the research perspective will be limited. This study designs a two-stage network DEA model to measure the innovation capability of organizations. It decomposes the innovation capability into the innovation development and innovation transformation stages based on the innovation value chain perspective. I develop the innovation capability measurement indexes objectively and systematically using the innovation value chain theory and DEA model, which to some extent corrects the subjectivity in previous similar studies and analyzes what is in the "black box" of innovation capability.

The total innovation capability of China's new energy vehicle industry is now weak, according to this study, and prior subsidy policies have not effectively fostered but rather impeded China's new energy vehicle industry's innovation capability. Government subsidies, when compared to market-based income distribution, are a form of income redistribution that raises transaction costs in a variety of ways, including policy design, policy implementation, policy exit, and rent-seeking costs (Wang et al. 2021). Because of these transaction expenses, government subsidies are generally ineffective in promoting the industry's innovation capability.

The Chinese government's subsidy policy for the new energy vehicle industry has begun to show a receding trend (Ye et al. 2021), indicating that the Chinese government's approach to the growth of the new energy vehicle industry is sensible, and also partially justifying the findings of this study. In the context of the subsidy retreat, government subsidies should abandon past policy instruments that were solely aimed at expanding the scale of the industry, improve the subsidy allocation mechanism in response to China's current problems with new energy vehicle technology development, and implement a talent-oriented subsidy allocation system that focuses on the guiding and leveraging role of subsidies.

To improve their innovation capability, it is necessary to curb enterprises' motivation to cheat on subsidies from the source, stimulate their independent innovation, guide them to increase their awareness of R&D investment, focus on the output of market-oriented technological innovation results, and improve the technology conversion rate. China's new energy vehicle industry got off to a late start, and the current government subsidy monitoring mechanism has issues with information asymmetry and an ineffective supervision system (Luo et al. 2021). Simultaneously, a talent-centered subsidy mechanism should be implemented as much as feasible in accordance with the supply of talent, which corresponds to the skills required for industrial development. This is the key to effectively converting innovation inputs into innovation outputs. To achieve a talent-centered subsidy mechanism, it is critical to conduct regular assessments of new energy vehicle enterprises' innovation capabilities and to differentiate subsidies for enterprises based on their innovation capability levels in order to fully exploit the synergy between talent and government subsidies for the development of enterprises' innovation capabilities.

ACKNOWLEDGMENTS

This study was supported by the Educational research project for young and middle-aged teachers of the Fujian Provincial Department of Education (JAS20486) and the Fujian new liberal arts research and reform practice project "Construction practice of new liberal arts in the field of Applied Undergraduate Economic management law."

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